Early Chronic Illness Detection

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1 Abstract

Globally, an estimated 3.8% of the population experiences depression, including 5% of adults and 5.7% of adults older than 60 years. India's suicide rate is among the highest globally, with an estimated 21.1 suicides per 100,000 people, highlighting the severe impact of untreated mental health issues. Depression is a leading cause of disability worldwide, contributing significantly to the global burden of disease, and in India, it is pushing around 20% of households into poverty due to high healthcare costs. Timely detection of depression is crucial for preventing severe mental health conditions and enabling more cost-effective treatments.

GitHub Link

2 Introduction

This project aims to develop a cost-effective and holistic solution for depression detection by incorporating socioeconomic, health, and lifestyle data. By analyzing this comprehensive dataset, we seek to improve prediction accuracy and provide deeper insights into the relationship between these factors and chronic illness, enabling more accurate early detection and intervention strategies.

3 Literature Review

3.1 Depression Detection Using Machine Learning (Chauhan et al. 2023)

This study establishes a relationship between stress-related factors and depression detection using machine learning, focusing on identifying individuals with high stress levels who may not show visible symptoms of depression [2]

3.2 Neuroimaging-Based Detection (Fu et al. 2018)

Fu et al. utilized machine learning on neuroimaging data to detect depression with 86% accuracy by identifying brain structural changes, using cross-validation for robust results [3].

3.3 A comparative study of different classifiers for detecting depression from spontaneous speech

This research employed Support Vector Machines (SVM) and Natural Language Processing (NLP) to analyze speech features, such as slower rates and longer pauses, achieving 80% accuracy in predicting depression [1]

4 Dataset Description

4.1 Data Collection

The primary source of our dataset is a Kaggle Dataset authored by Anthony Therrien, designed to facilitate the analysis of individuals' health, lifestyle, and socioeconomic factors in relation to depression detection.

4.2 Data Features

Important Demographic Information and Personal Attributes:

- **Education Level:** Associate Degree (19.33%), Bachelor's Degree (32.71%), High School (22.81%), Master's Degree (21.15%).
- **Marital Status:** Divorced (7.91%), Married (58.11%), Single (17.43%), Widowed (16.55%).
- **Smoking Status:** Former Smoker (26.67%), Nonsmoker (60.72%), Smoker (12.61%).
- **Physical Activity Level:** Active (26.68%), Moderate (31.64%), Sedentary (41.68%).
- **Alcohol Consumption:** Low (22.72%), Moderate (46.80%), High (30.48%).
- **Dietary Habits:** Ranges from healthy to unhealthy eating patterns.
- **Sleep Patterns:** Fair (41.73%), Good (39.48%), Poor (18.79%).
- **Employment Status:** Describes whether the individual is employed or unemployed.
- **Income:** Income ranges from $0.41 to $209,995.22, with an average income of $50,661.71.

- **History of Mental Illness:** Yes (45.59%), No (54.41%).
- **History of Substance Abuse:** Indicates whether the individual has a history of substance abuse.
- **Family History of Depression:** Yes (26.89%), No (73.11%).
- **Chronic Medical Conditions:** Yes (32.92%), No (67.08%).

4.3 Data Distribution

The dataset consists of 413,768 entries and contains 16 columns, including a label for Chronic Disease, which is categorized as 'Yes' or 'No'.

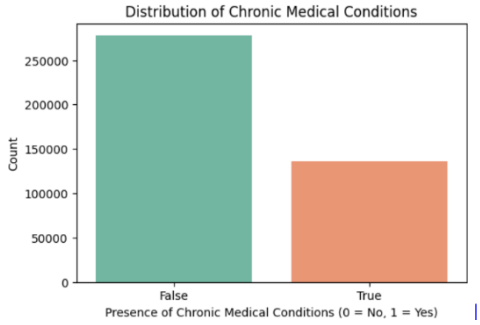


Figure 1: The distribution of chronic medical conditions shows a higher count of individuals labeled 'No'67% compared to those labeled 'Yes'33%

EDA Pattern Detection in Data

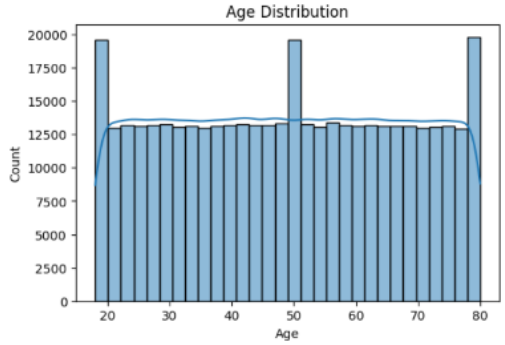


Figure 2: The distribution of chronic medical conditions shows a higher count of individuals labeled 'No'67% compared to those labeled 'Yes'33%

4.4 Data Pre-Processing

- Class Imbalance - occurs as "No" (those without chronic conditions) has significantly more instances than "Yes"(those with chronic conditions) [1]. So to balance the dataset we use SMOTE

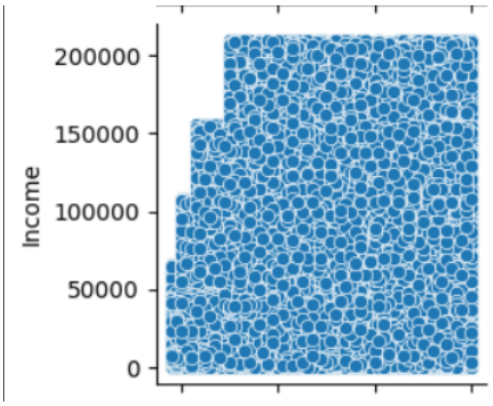


Figure 3: Age distribution shows peaks at 20, 50, and 80, suggesting targeted survey samples.] Relationships between age, income, lifestyle, and chronic conditions are likely non-linear in health data.

- Standardization - of the dataset to improve the model predictions and accuracy later on however minor tweaking is expected to be needed as we move on further into the project.
- Encoding was needed for the varchar values (Categorical Value) ie: Marital Status, Education Level, Smoking Status, Employment Status and Alcohol Consumption etc in the dataset so we have used one-hot encoding for it
- Missing values were printed however the dataset has no NaN or missing values hence not needed to be removed/ replaced with the average.
- Non Linear Relationships : Some feature like age [2] and income shows non linear relationships so Feature engineering can improve the predictive power of the model by helping it better understand the relationships between variables that are not linearly related.

5 Methodology

5.1 Logistic Regression with Batch Gradient Descent (BGD)

- **Parameters:** `solver='lbfgs', max_iter=1000, class_weight='balanced', random_state=42`.
- Applied to handle class imbalance using class weights and trained on scaled data for better convergence. BGD provides stable weight updates by processing the entire dataset at each iteration.

5.2 Logistic Regression with Stochastic Gradient Descent (SGD)

- **Parameters**: `loss='log_loss', max_iter=1000, tol=1e-3, class_weight='balanced', random_state=42`.

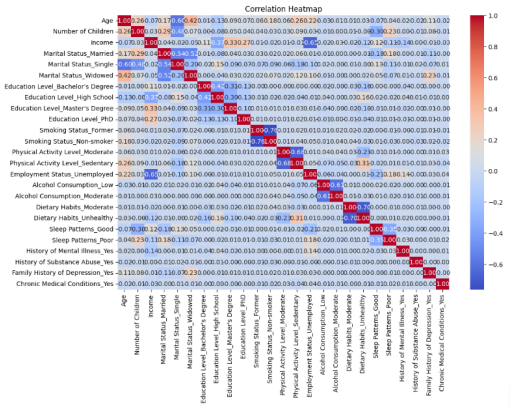


Figure 4: Positive correlations (in red) indicate that as one factor increases, so does the other, such as income and employment or physical activity and good sleep. Negative correlations (in blue) show an inverse relationship, where an increase in one factor leads to a decrease in another, such as unemployment with income or poor sleep patterns with physical activity and healthy habits.

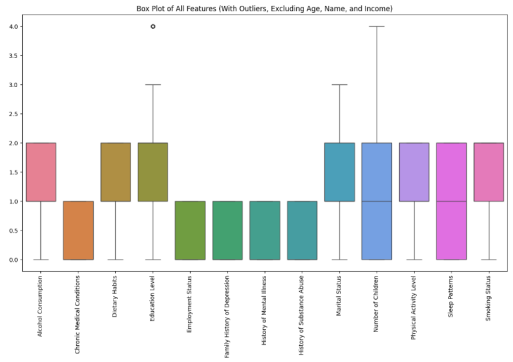


Figure 5: This boxplot detects no outliers in the data

- Faster but noisier compared to BGD, with updates on individual samples. Used to explore faster training possibilities on scaled data.

5.3 Ridge Logistic Regression with Recursive Feature Elimination (RFE)

- **Parameters**: `penalty='l2', n_features_to_select=5, max_iter=1000, class_weight='balanced', random_state=42`.
- RFE selects top features, and L2 regularization penalizes large coefficients to prevent overfitting.

5.4 Principal Component Analysis (PCA)

- **Parameters**: `n_components=10`.
- Reduced dimensionality while retaining most variance (explained variance ratio). Applied to simplify models and improve performance.

5.5 Optimal Threshold Tuning

- Calculated the optimal threshold to maximize the difference between TPR and FPR, improving classification for imbalanced data.

5.6 Random Forest (Tuned)

- **Parameters**: `n_estimators=200, max_depth=20, min_samples_split=5, min_samples_leaf=2, class_weight='balanced'`.
- Tuned to optimize performance with hyperparameter adjustments for better generalization.

5.7 Decision Tree Classifier

- **Parameters**: `n_estimators=200, max_depth=20, min_samples_split=5, min_samples_leaf=2, class_weight='balanced'`.
- Trained using GridSearchCV on SMOTE-balanced data. Effective at capturing non-linear patterns with controlled overfitting.

5.8 Naive Bayes (Gaussian and Bernoulli)

- **Gaussian Naive Bayes**: Assumes features follow a normal distribution, suitable for continuous data.
- **Bernoulli Naive Bayes**: Trained on binary-transformed features (values 0).
- Both models took advantage of feature independence.

5.9 MLP Classifier (Neural Network) with Multiple Activation Functions

A classifier (MLP) was applied to assess the impact of various activation functions including **'identity', 'logistic', 'tanh', and 'relu'** on model performance

- **Parameters**: Two hidden layers with 100 and 50 neurons, 'adam' solver, a maximum of 300 iterations, early stopping enabled with no improvement stopping after 10 iterations, ensuring the model avoids overfitting.

5.10 AdaBoost Implementation

Utilized a Decision Tree Classifier (stump) as the base estimator with 100 boosting rounds, computed feature importance, and analyzed training-validation error trends for performance insights.

5.11 Voting Classifier

It implements ensemble learning by combining the predictions of three individual models- Logistic Regression, Decision Tree Classifier ,Gaussian Naive Bayes.
Hyper-parameters:

- Logistic Regression: classweight='balanced' accounts for class imbalance, and maxiter=1000 ensures sufficient iterations for convergence.
- Decision Tree: maxdepth=5 limits the tree's depth, controlling overfitting and complexity.
- Gaussian Naive Bayes: Assumes a Gaussian distribution for continuous features.

5.12 XgBOOST

XGBoost Classifier Configuration: Implemented 200 boosting rounds with a maximum tree depth of 4, learning rate of 0.1, and sampling ratios (colsamplebytree=0.8, subsample=0.8) to enhance generalization and prevent overfitting.

5.13 Linear Discriminant Analysis (LDA)

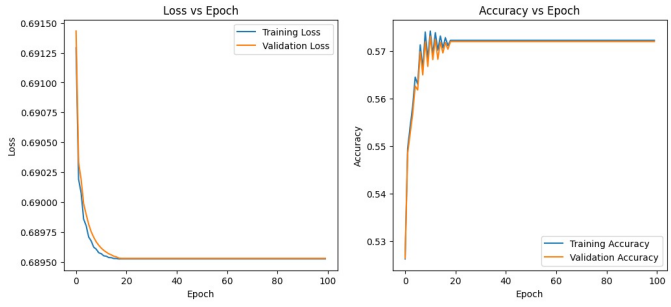
It works by finding a linear combination of features that best separates the classes. It assumes that the data from each class has a Gaussian distribution with identical covariance matrices.

5.14 Quadratic Discriminant Analysis (QDA)

An extension of LDA that allows each class to have its own covariance matrix, making it suitable for problems with non-linear boundaries.

6 Results

Plot Loss vs epoch ad accuracy vs epoch on logistics regression



Adaboost

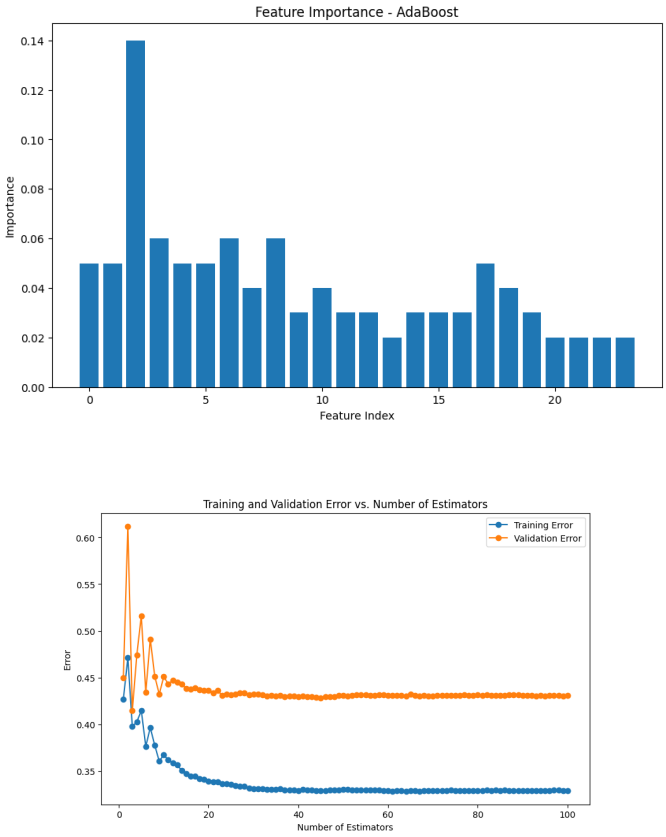


Figure 6: loss Function Plot for AdaBoost (e.g., Chronic Medical Conditions).

7 Post Midsem Results Analysis

7.1 Voting Classifier

- Accuracy: 60.1
- Strengths: Combines predictions from multiple models (Logistic Regression, Decision Tree, and Naive Bayes) using soft voting, leveraging their strengths.

7.2 Linear Discriminant Analysis (LDA)

- Accuracy: 59.95%
- Strengths: Performs well with linearly separable data and balances precision and recall fairly well.

7.3 Quadratic Discriminant Analysis (QDA)

- Accuracy: 61.8%
- Strengths: Outperforms LDA and the Voting Classifier by capturing some non-linear relationships. Precision is higher compared to LDA.

7.4 AdaBoost

- Accuracy: 56.9%

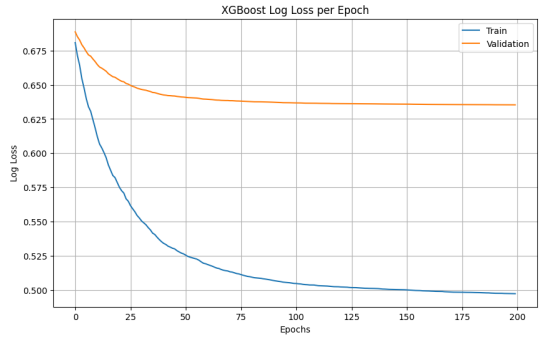


Figure 7: XGBoost Log Loss per Epoch Curve

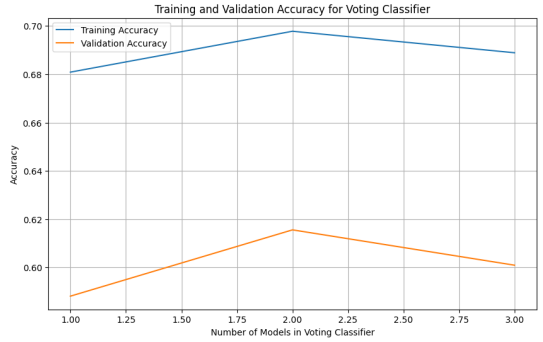


Figure 8: Voting Classifier ACCURACY: 60.10%

- Strengths: Boosts weak learners iteratively, showing decent recall compared to other methods like XGBoost.

7.5 XGBoost

- Accuracy: 66.8%
- Strengths: Gradient boosting with optimized decision trees leads to better performance than other techniques.

8 Conclusion

- **MLP with Non-linear Activation Functions (67% Accuracy):** Non-linear activation functions (e.g., ReLU) capture complex patterns in data, while a multi-layer architecture learns hierarchical representations. The Adam optimizer ensures robust and faster convergence.
- **XGBoost (67% Accuracy):**XGBoost leverages gradient boosting for iterative error correction, assigns feature importance for noise reduction, and uses regularization and subsampling techniques to balance overfitting and generalization.

9 Individual Contribution

- **Satyam**: Decision Tree, MLP, AdaBoost

Machine Learning Technique	Accuracy(%)
Logistic Regression with Batch Gradient Descent (BGD)	57
Logistic Regression with Stochastic Gradient Descent (SGD)	52
L2 (Ridge) Logistic Regression with Recursive Feature Elimination (RFE)	57
Logistic Regression with PCA	54
Logistic Regression with SMOTE and OPTIMAL THRESHOLD	60
Random Forest (Default parameters)	59
Random Forest (Tuned)	61
Decision Tree Classifier [CRITERIAN='GINI']	57
Decision Tree Classifier [CRITERIAN='ENTROPY']	63
Naive Bayes (Gaussian)	67
Naive Bayes (Bernoulli)	67
MLP Classifier('IDENTITY')	58
MLP Classifier('LOGISTIC','TANH','RELU')	66

Figure 9: Pre MidSem Results

- **Aditya**: Logistic Regression, Decision Tree, LDA, QDA
- **Suyash**: Random Forest, Model Evaluation, Voting Classifier
- **Vickey**: Naive Bayes, Data Preprocessing, XGBoost
- **Satyam Pandey**: Documentation, EDA

References

[1] Sharifa Alghowinem, Roland Goecke, Michael Wagner, Julien Epps, Tom Gedeon, Michael Breakspear, and Gordon Parker. A comparative study of different classifiers for detecting depression from spontaneous speech. In *2013 IEEE International Conference on Acoustics, Speech and Signal Processing*, pages 8022–8026, 2013. 1

[2] Nikhil Chauhan and Divya Rani Swati. Depression detection using ml. 1

[3] Sergi G Costafreda, Carlton Chu, John Ashburner, and Cynthia HY Fu. Prognostic and diagnostic potential of the structural neuroanatomy of depression. *PloS one*, 4(7):e6353, 2009. 1